Water Quality Analysis based on Remote Sensing Data and Numerical Model

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Abstract

To analyze the relationship between temporary changes in water current and water pollution, we constructed a numerical model for drift current in this paper. Water quality estimation maps were also drawn by fuzzy regression analysis between remote sensing data and water quality measurements. Lake Hachiro in Akita was selected as the test site for the case study. Computer simulation result of the flow vector agreed well with the water quality estimation maps. It can be concluded that drift current helps clarify water quality.

Key words : water quality, drift current, water quality estimation map, remote sensing data

I. Introduction

Water pollution in lakes, marshes, and rivers is increasing, making the monitoring of water quality particularly important. Water quality is usually studied by collecting water directly at measurement sites. A direct survey of wide areas such as lakes is neither practical nor economical. A synoptic view from remote sensing data is useful in understanding water quality (Tanaka *et al.*, 1990). Therefore, water quality was analyzed using remote sensing data (Inomata and Ogata, 1990; Miyazaki *et al.*, 1991; Oki and Yasuoka, 1997). Clouds may adversely influence optical sensors such as the Landsat Thematic Mapper (TM), and remote sensing data shows only temporary water quality. To observe water quality continuously, water movement in lakes should be considered in addition to remote sensing data. We studied the relationship between water quality estimation maps

by fuzzy regression analysis and the drift current computed by a numerical model for Lake Hachiro, Akita.

II. Test Site and Data Acquisition

Lake Hachiro in Akita, Japan, was selected as the test site. The lake is located in north-west of Akita-city. Ogata village was reclaimed land extending 18-km from north to south and 12-km from east to west. Figure 1 shows the outline of Lake Hachiro and the measurement sites of water quality. Seven measurement sites (St. 1 to St. 7) are used.

Seven water quality parameters were measured on June 8, 1994 at seven sites (Table 1). They were hydrogen-ion indicator (pH), dissolved oxygen (DO), biochemical oxygen demand (BOD), chemical oxygen demand (COD), suspended solids (SS), total nitrogen (T-N), and total phosphorus (T-P).

Landsat TM data on June 16, 1994 was analyzed; twenty-five pixels around each

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Fig. 1 Outline of Lake Hachiro and the measurement sites of water quality. Lake Hachiro is located in northwest of Akita-city, Japan. There are seven measurement sites of water quality for analysis (St. 1 to St. 7).

Table 1 Measurements of water quality.

Measurement site of water quality	Water quality						
	PH	DO	BOD	COD	SS	T-N	T-P
1. Hamaguchi drain pumpsite	7.4	9.2	3.2	3.5	14	0.90	0.06
2. Noishi bridge	8.3	10.0	12.0	6.7	34	1.10	0.10
3. Ogata bridge	7.7	9.5	3.4	2.8	6	0.63	0.05
4. South drain pumpsite	7.8	9.3	6.0	1.7	16	0.36	0.05
5. Gate	7.8	9.6	7.5	2.5	15	0.53	0.11
6. East site	7.8	9.1	5.0	2.2	13	0.34	0.04
7. Center site	7.8	9.3	5.7	1.7	25	0.39	0.07

pH: hydrogen-ion indicator, DO: dissolved oxygen, BOD: biochemical oxygen demand, COD: chemical oxygen demand, SS: suspended solids, T-N: total nitrogen, T-P: total phosphorus.

*Dimension of water quality: *mg/l* (except PH)

measurement site were obtained by the operator. Table 2 shows the average and standard deviation of TM CCT count number (luminous intensity) at measurement sites; sixth-band TM data was excluded due to its different resolution. Data acquisition for water quality differed from Landsat TM data. Although

2-mm of rainfall occurred on June 14, 1994, at Ogata village, it was considered that the influence of the rainfall on water quality trends is very little.

Weather data for the day on which TM data was taken was used for computer simulation. The wind velocity and direction

Table 2 Average and Standard deviation of the CCT count number of TM-band at measurement sites.

Measurement site of water quality	Landsat TM data					
	Band 1	Band 2	Band 3	Band 4	Band 5	Band 7
1. Hamaguchi drain pumpsite	75.680 (1.287)	26.600 (0.894)	23.640 (0.557)	13.200 (0.490)	5.440 (0.852)	1.880 (0.711)
2. Noishi bridge	78.880 (1.211)	28.040 (0.720)	27.240 (1.242)	14.840 (2.344)	9.440 (1.920)	3.000 (1.166)
3. Ogata bridge	74.400 (1.265)	24.320 (0.614)	20.560 (0.753)	11.080 (0.560)	5.320 (1.256)	1.400 (0.693)
4. South drain pumpsite	81.560 (1.472)	31.040 (0.528)	28.880 (0.711)	12.000 (0.490)	4.840 (0.880)	1.720 (1.950)
5. Gate	77.320 (1.009)	27.840 (0.543)	24.960 (0.599)	11.920 (1.197)	5.760 (1.209)	1.880 (1.681)
6. East site	78.120 (1.107)	28.840 (0.463)	24.240 (0.512)	11.360 (0.625)	5.000 (0.980)	0.880 (0.711)
7. Center site	81.120 (0.993)	30.880 (0.816)	27.840 (1.376)	11.680 (0.546)	5.120 (0.816)	1.360 (1.015)

(): Standard deviation.

Landsat TM data taken on June 16, 1994 was used in this paper. Twenty-five pixels around the measurement site for water quality were obtained by the operator.

registered 1.7m/s NNW on June 16, 1994.

III. Data Analysis

1) Fuzzy regression model

The fuzzy regression model assumes that the difference between observation data and the model indicates system fuzziness, showing the relationship of input and output (Ishibuchi, 1992). Remote sensing data includes external disturbance components, *e.g.*, path radiance, sun glitter, atmosphere scattering and absorption, water surface waves, and sensing system noise (Yokoyama, 1983). It is necessary to consider fuzziness in data processing. It is difficult to specify measurement sites in images because the resolution ability of LANDSAT TM is 30-m. Given these restrictions, the CCT count number distribution includes fuzziness. We assume that the distribution of the CCT count number is a fuzzy number.

In this paper, fuzzy regression analysis was conducted using both remote sensing data and

measurements of water quality parameters. The fuzzy regression model was computed using the following equation (Nishida *et al.*, 1995):

$$Y(X_p) = A_0 + A_1 X_{p1} + \dots + A_n X_{pn} \quad (1)$$

$$= (a(X_p), e(X_p))_L \quad (2)$$

where

$$a(X_p) = a_0 + a_1 X_{p1} + \dots + a_n X_{pn} \quad (3)$$

$$e(X_p) = e_0 + e_1 |X_{p1}| + \dots + e_n |X_{pn}| \quad (4)$$

A_i is a fuzzy coefficient, $Y(X_p)$ is an estimate (fuzzy number), $a(X_p)$ is the center (mean) of $Y(X_p)$, and $e(X_p)$ is the width of $Y(X_p)$. Equation (2) is the fuzzy regression model with the center and width of the fuzzy number. Since the fuzzy regression model is the one-input and one-output, four variables (a_0, e_0, a_1, e_1) are obtained by the following equations:

$$Y(X_p) = A_0 + A_1 X_p \quad (5)$$

$$= (a_0, e_0)_L + (a_1, e_1)_L X_p \quad (6)$$

where X_p is the measurements of water quality, A_1 the triangular fuzzy number, a_1 the center of the fuzzy number, e_1 the width

Fig. 2 Measurement value and triangular fuzzy number of the CCT count number.

The triangular fuzzy number was produced by a vertex (a_1) and the width (e_1), which was twice the standard deviation (σ).

of the fuzzy number, and $Y(X_p)$ the estimation fuzzy output interval. The mean CCT count number and the triangular fuzzy number were used for analysis. The triangular fuzzy number was produced by a vertex (a_1) and the width (e_1), which was twice the standard deviation (σ) is shown in Fig. 2.

2) Fuzzy level-slice processing

The fuzzy output interval obtained by the fuzzy regression model shows that the CCT count number corresponds to the forecasted range obtained by measuring water quality parameters. It has already clarified that water quality estimation maps by using fuzzy level-slice processing can show the intermediate levels of water quality in comparison with conventional level-slice processing (Nishida and Otsuka, 1995). In order to understand water quality in detail, the estimation maps in this paper were drawn by means of fuzzy level-slice processing. The technique employs simplification fuzzy reasoning (Mizumoto, 1992).

We assume that the CCT count number shows the possibility of corresponding to the specific level of water pollution that set in optional range. The production rule for

estimating water quality in the pixel is as follows:

$$\begin{aligned} \text{Rule 1: } & Y_1 \rightarrow Z_1 \\ & \dots \dots \dots \\ \text{Rule n: } & Y_n \rightarrow Z_n \\ \text{Input: } & S \\ \text{Output: } & Z_0 \end{aligned} \quad (7)$$

where Y_i ($i=1, \dots, n$) is an estimation fuzzy set of the CCT count number in proportion to the slice level, and Z_i ($i=1, \dots, n$) is water quality in each rule. S is the input of the CCT count number. Z_0 is the output. Output Z_0 is given by

$$Z_0 = \frac{\sum_{i=1}^n h_i Z_i}{\sum_{i=1}^n h_i} \quad (8)$$

When input S is given, h_i is the ratio for getting the Z_i . Rule number corresponds to the slice number. The slice number was six in this paper.

3) Numerical model

A stream is the flow of water, caused by factors such as wind, water inflow and outflow, heat, attraction (gravity), and atmospheric pressure. These factors influence each other and flows are created by control factors, *e.g.*, Coriolis force caused by the form of lakes, water surface, water depth, and global rotation.

Water quality distribution shows the concentration of chemicals, *e.g.*, suspended solids and total nitrogen. The water current gives rise to mixing and diffusion of water quality. It is reported that wind causes the water current in lakes (Tanaka *et al.*, 1990). Therefore, numerical simulation was conducted to analyze the relationship between water current and quality. The numerical model for the drift current was constructed using a finite element method. The flow numerical analysis

model in dimension 2 accounts for the following assumptions (Tanaka *et al.*, 1990; Onishi *et al.*, 1986):

- (1) The vertical change in water is minimal because all of Lake Hachiro is shallow.
- (2) Water density is constant.
- (3) Pressure distribution is steady.
- (4) Atmospheric pressure is almost constant.

The drift current is expressed as follows:

$$\frac{\partial M}{\partial t} = fN - g(h + \zeta) \frac{\partial \zeta}{\partial x} + \frac{1}{\rho_w} (\tau_x(s) - \tau_x(b)) \quad (9)$$

$$\frac{\partial N}{\partial t} = fM - g(h + \zeta) \frac{\partial \zeta}{\partial y} + \frac{1}{\rho_w} (\tau_y(s) - \tau_y(b)) \quad (10)$$

$$\frac{\partial \zeta}{\partial t} + \frac{\partial M}{\partial x} + \frac{\partial N}{\partial y} = 0 \quad (11)$$

where

M is the flux in direction x and N that in direction y : $M = (h + \zeta)U$, $N = (h + \zeta)V$.

U is the mean flow velocity in direction x and V that in direction y .

f is the Coriolis force: $f = 2\omega \sin \phi$.

ω is the angular velocity of global rotation.
 ϕ is latitude.

ζ is the height between data plane and water surface.

h is the water depth between data plane and

bottom.

$\tau_x(b)$, $\tau_y(b)$ is the shear at the bottom in directions x and y .

$\tau_x(s)$, $\tau_y(s)$ is the shear on the water surface in directions x and y .

Shear is obtained by the following equation.

$$\tau_{x \text{ or } y}(b) = \rho_w \gamma_b^2 U_{\text{or } V} \sqrt{U^2 + V^2} - \beta \tau_{x \text{ or } y}(s) \quad (12)$$

$$\tau_{x \text{ or } y}(s) = \rho_a \gamma_a^2 W_{x \text{ or } y} \sqrt{W_x^2 + W_y^2} \quad (13)$$

ρ_a is atmospheric density.

ρ_w is water density.

$$\gamma_a^2 = 1.3 \times 10^{-3}.$$

$$\gamma_b^2 = 2.6 \times 10^{-3}.$$

$$\beta = 1.0.$$

W_x , W_y is the wind velocity in directions x and y . Computer simulations for the drift current were conducted under the initial condition that $M=0$, $N=0$, $\zeta=0$.

Figure 3 shows the flowchart for data analysis in this paper.

IV. Results and Discussion

1) Fuzzy regression analysis result

Since the fuzzy regression model analyzes a one-input and one-output system, four variables (a_0 , e_0 , a_1 , e_1) must be obtained. When the complete solution or the objective function was not determined, the complete fuzzy regression analysis result was not obtained. Table 3 shows the result of fuzzy regression analysis with average number. The solution of ten sets was obtained. When the fuzzy number of remote sensing data is used for analysis, it is also necessary to solve min and max problems (Ishibuchi, 1992). The complete result (four variables) for the min problem is shown in Table 4 (eleven sets) and the complete result for the max problem (seven sets) in Table 5. In water quality parameters, DO is not related to the CCT count number of TM data. Two combinations-

Fig. 3 Flowchart for data analysis.

This paper investigates the relationship between the water quality estimation map using Landsat TM data and measurements of water quality, and the drift current computed by a numerical model.

Table 3 Result of fuzzy regression analysis with average number.

No	TM Band	Water quality parameter	Objective Function	a_0	a_1	e_0	e_1
1	1	pH	22.447	16.907	7.878	0	0.411
2	4	SS	7.166	11.471	0.057	0.581	0.025
3	4	T-N	6.598	10.618	2.285	0	1.553
4	4	T-P	7.740	10.560	27.500	0.180	13.500
5	5	BOD	3.723	3.651	0.688	0	0.176
6	5	SS	7.468	4.390	0.089	0.047	0.058
7	5	T-N	6.689	3.014	4.269	0	1.573
8	5	T-P	9.216	4.000	35.200	0	19.200
9	7	SS	3.560	0.728	0.048	0.368	0.008
10	7	T-P	3.175	0.374	19.943	0.006	5.657

Ten sets of the results are obtained with average number.

Table 4 Result of fuzzy regression analysis with fuzzy number (Min problem).

No	TM Band	Water quality parameter	Objective Function	a_0	a_1	e_0	e_1
11	1	pH	41.543	12.991	8.408	0	0.761
12	4	COD	21.974	11.278	0.251	0.958	0.357
13	4	BOD	18.724	10.182	0.695	1.029	0.546
14	4	SS	19.662	9.831	0.147	0.799	0.114
15	4	T-N	19.447	9.369	4.973	0.425	3.875
16	4	T-P	23.831	10.322	42.415	0	49.648
17	5	COD	22.580	3.855	0.404	1.823	0.229
18	5	BOD	20.445	2.972	0.965	2.169	0.249
19	5	SS	24.263	4.510	0.120	2.155	0.075
20	5	T-N	22.243	3.722	3.758	0.410	4.558
21	5	T-P	24.487	2.555	57.117	0.192	48.217

Eleven sets of the results are obtained by solving the Min problem.

Table 5 Result of fuzzy regression analysis with fuzzy number (Min problem).

No	TM Band	Water quality parameter	Objective Function	a_0	a_1	e_0	e_1
22	4	BOD	-1.683	9.887	0.746	0	0.080
23	4	SS	-0.970	12.019	0.022	0	0.008
24	4	T-P	-1.064	10.770	26.383	0	2.217
25	5	COD	-8.100	3.058	0.401	0	0.189
26	7	COD	-7.708	0.382	0.204	0	0.180
27	7	SS	-7.773	0.717	0.051	0.406	0.040
28	7	T-P	-9.923	0.497	20.758	0.354	15.508

Seven sets of the results are obtained by solving the Max problem.

Table 6 Correlation coefficient between water quality and the CCT count number of TM data.

	Band 1	Band 2	Band 3	Band 4	Band 5	Band 7
PH	0.412	0.253	0.462	0.497	0.786	0.579
DO	-0.050	-0.229	0.125	0.638	0.882	0.847
BOD	0.399	0.274	0.550	0.700	0.862	0.777
COD	-0.204	-0.329	0.012	0.894	0.958	0.858
SS	0.574	0.474	0.708	0.750	0.755	0.686
T-N	-0.402	-0.497	-0.152	0.860	0.804	0.826
T-P	0.050	-0.004	0.253	0.527	0.636	0.706

The correlation coefficient between the pollution concentration of water quality and the CCT count number of first, second and third band is low. The resulting correlation coefficient on fourth, fifth and seventh band is high, especially for the correlation coefficient on the fifth band.

SS and fourth-band TM data, and T-N and fourth-band TM data-obtain the complete results even using the average or the fuzzy number (both min and max problems). In addition to fourth-band TM data, fifth-band TM data gets the fuzzy regression analysis result.

To compare measurements of water quality and the CCT count number of TM data, the correlation coefficient was computed (Table 6). The correlation coefficient between the pollution concentration of water quality and the CCT count number of first, second and third band is low. The resulting correlation coefficient on fourth, fifth and seventh band is high, especially for the correlation coefficient on the fifth band. These spectral bands of TM data are related to measurements of water quality in this paper.

2) Comparison of results

Landsat TM image at the test site is shown in Fig. 4. Points A, B, and C are regions set for the examination. Typical examples of water quality estimation map are shown in Figs. 5--SS and CCT count number of fifth-band TM data--and 6. --T-N and CCT count

number of fifth-band TM data. The pollution level of water quality in estimation maps from point A to point C is remarkably high, especially the resulting using T-N and fifth-band TM data (Fig. 6).

The distribution of the flow vector is shown in Fig. 7. The drift downwind current exists throughout the lake. An annulus flow also occurs around points A, B, and C. Little water circulation may occur at these points, indicating that little circulation may increase pollution at all points. The simulation result for the numerical model corresponds to the water pollution in the estimation maps. Although both water inflow and effluent influence water quality at influx and efflux, the stagnating flow pollutes water quality. That is to say, the entire Lake Hachiro is greatly influenced by drift current.

V. Conclusion

To analyze the relationship between temporary change of water current and the pollution of water quality, we constructed a numerical model for drift current. Water quality estimation maps were also drawn

Fig. 4 Landsat TM image at the test site(R, G, B: Band 4,5,7). Landsat TM data was taken on June 16, 1994. Points A, B, and C are regions set for the examination.

Fig. 5 Water quality estimation map for fuzzy level-slice processing. The estimation map is obtained using SS and the CCT count number of fifth-band TM data.

Fig. 6 Water quality estimation map for fuzzy level-slice processing. The estimation map is obtained using T-N and the CCT count number of fifth-band TM data.

Fig. 7 Distribution of flow vectors. The drift downwind current exists throughout the lake. An annulus flow also occurs around points A, B, and C. Little water circulation may occur at these points, indicating that little circulation may increase pollution at all points.

using fuzzy regression analysis between remote sensing data and measurements of water quality. Lake Hachiro in Akita was the test site for the case study. Computer simulation result of the flow vector agreed well with the water quality estimation maps. It can be concluded that drift current helps clarify water quality.

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リモートセンシングデータと数値モデルを用いた水質分布解析

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近年、地球環境保護の見地から湖沼および河川における水質汚濁状況のモニタリングの必要性が高まり、広域性に優れた特徴を有するリモートセンシングデータの水質分布解析への利用が期待されている。しかしながら、ランドサット衛星のThematic Mapper (TM) センサなどといった光学センサにより取得されるリモートセンシングデータは雲の影響を受けやすく、利用可能な時系列データの取得は困難である場合が多い。さらに、リモートセンシングデータのとらえる状況は瞬時情報であるため、水質状況をより適切に把握するためには水の流動を合わせて考慮する必要がある。

そこで本論文では秋田県の八郎湖を対象とし、風により引き起こされる水の流れ、すなわち吹送流が八郎湖における水質分布変化の最大要因と仮定して検討を加えた。具体的には吹送流の数値モ

デルを作成してシミュレーションを行い、水質分布図との対応について検討を加えた。なお、本論文では種々のあいまいさを考慮するため、リモートセンシングデータをファジィ数と見なした。すなわち、測定された少数の水質データを有効に活用するため、水質データとリモートセンシングデータに関するファジィ回帰モデルを作成し、解析を行った。さらに、得られた解に対してファジィレベルスライス処理を施し、水質分布図を作成した。

得られた結果について比較検討を行ったところ、吹送流のシミュレーション結果と水質分布図の間には関連性が認められた。また、八郎湖は風による湖水の移動が主であり、汚濁物質の溜まりやすい場所の流動が少ないこと、流れの淀む地点における水質汚濁の著しいことなどが明らかとなった。

キーワード：水質、吹送流、水質分布図、リモートセンシングデータ

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